2024 IEEE International Conference on Contemporary Computing and Communications (InC4)

# Enhanced Retinal Vessel Segmentation using U-Net Framework

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***Abstract*—The key step in retinal imaging is blood vessel augmentation, which is important for early diagnosing eye conditions such as glaucoma, macular edema, diabetic retinopathy, and more. Deep learning has been used in the segmentation process for the last few years due to its high accuracyand efficiency. We have proposed a convolutional neural networkbased on U-net to segment blood vessel fundus images in this paper. The publicly available DRIVE and CHASE DB1 datasets were used to train the model and for testing, the HRF dataset was used. For the DRIVE dataset, the research findings show an average accuracy of 93.2 percent.**

***Index Terms*—Retinal fundus image, Blood vessel segmentation, Deep Learning, U-Net-based Convolutional neural network (CNN)**

## I. Introduction

The human eye is like a camera. It helps us to see and understand our surroundings. The retina is an important part of the human eye which is located at the back of the eye. It acts like a sensitive screen and is necessary for us to see things. The thick vessels that carry blood to the retina are called retinal blood vessels. The nutrients in these vessels are essential for life. The retinal blood vessels are damaged due to various reasons like diabetes, high blood pressure, aging, smoking, eye injuries, etc. This may cause vision problems if not treated properly. To diagnose these causes, early detection and effective management of the underlying causes are necessary.

Need for Retinal blood vessel segmentation: In the diagnosis and treatment of retinal diseases such as hypertension, diabetes mellitus, etc, retinal blood vessel segmentation plays an important role. It is also a technique for extracting and visualizing blood vessels from fundus images. There are medical imaging techniques such as fundus imaging, fluorescein angiography, and OCT angiography are used in assessing the morphological properties of the retinal vessels. In this paper, we consider fundus images. For diagnosis of ocular diseases, fundus images are used that are captured with a fundus camera. Retinal vessel characteristics, including length, width, circumference, branch pattern, branch angle, etc can be used for screening, diagnosing, and measuring a wide range of eye conditions including atherosclerosis, diabetes, and hematology [1].

Role of deep learning: To decrease the damage of retinal blood vessels, detecting and diagnosing eye diseases at an early stage is important. The treatment is most effective when the ailment is detected in the early stage which enhances patient results. Poor vessel-to-background contrast, Complex vessel distribution, lesion interference, and uneven illumination in fundus images make retinal blood vessels difficult to classify and segment blood vessels manually. But this was a time-consuming, expensive, and laborious process. Researchers have developed several methods to classify retinal blood vessels to overcome this issue. Retinal blood vessel segmentation has shown impressive results through deep learning.

Deep learning is superior to traditional methods in many ways. Deep learning techniques automate feature learning with more data and less human interpretation. Because they are not tied to a specific application and can learn different layer patterns on their own, they have greater recognition and generalizability. This saves the time of doctors which helps them to focus on referable cases that improve the diagnosis. Deep learning is more accurate and faster because it can process more images quickly. This is important in applications such as diagnosing diabetic retinopathy screening. Therefore, using common datasets, this study proposes a U-net-based convolution neural network for retinal blood vessel segmentation and evaluates the performance considering standard available datasets.

Following is the paper arrangement:

1) *Section I is the introduction:*
2) *Section II includes the literature review:*
3) *Section III provides details on the dataset used:*
4) *Section IV describes the proposed methodology:*
5) *Section V presents the results:*
6) *Section VI concludes the analysis:*

## II. LITERATURE SURVEY

Several segmentation methods for retinal blood vessels have been published. In this section, we discuss segmentation methods. Blood vessel extraction was performed using standard imaging techniques such as tortuosity detection, edge detection, Gabor filter, and so on. As these methods were complex and time-consuming, the accuracy rates were not up to the mark, due to which many algorithms came into the spotlight. With the development of technologies, many procedures have been proposed which are classified into 2 algorithms known as supervised and unsupervised. These algorithms are classified as machine learning. When an encoder/decoder network configuration is used, the supervised method first down-samples the input image before upscaling it to its original size. Using this method, we obtain efficient classification results. Clustering techniques such as K-mean and fuzzy-c mean algorithms are implemented by unsupervised algorithms. In this algorithm, each pixel is assigned to a valid blood vessel group. As it was observed that machine learning techniques gave lesser accuracy rates and needed human involvement, Deep learning techniques were introduced to overcome such challenges.

Inspired by the DNN Architecture, a max pooling convolutional neural network(MPCNN) was implemented. Through several hierarchical and fully connected layers, this transforms input samples into output class probabilities for feature extraction and distribute derived features respectively [3]. Another novel model was proposed called sine-net. As to get thin and thick vessel features this model performs upsampling followed by downsampling. This method comes under a supervised algorithm. To get control of overfitting three methods were applied for data augmentation of the images which are Rotation translation and Mirroring operations [4].

Few researchers studied deep learning techniques i.e. deep neural network by using augmented data of available datasets (DRIVE, STARE) [5]. A multi-level and multi-scale based Deep Neural Network using Convolutional architecture was proposed and with minimum iterations, it was compared to the existing methods in the DS layers and augmented dataset. A large number of datasets is needed for training and testing processes, but it is very difficult to obtain medical image datasets. So the augmentation of the available dataset is done for better accuracy. The input images are augmented using various transformations referred to in this paper [6] [7].

Similarly, a CNN-based segmentation method was proposed. This architecture is made of fully connected layer, 3 pooling layers and three convolution layers. They used several CNNs to recognize each pixel in multiple scales to get better performance [3]. Three pre-processing algorithms—a masking method, an image enhancement algorithm, and a method to crop images into 64X64 pixels were adjusted to segment input images. After pre-processing, the model is applied to extracted patches of the images [8]. To improve accuracy and parameter selection, improved optimization techniques for the CNN model were introduced [9] [10].

The authors of [10] have illustrated an automatic retinal vessel segmentation framework using multi-path, multi-scale, and multi-output fusion FCN (M3FCN) for the segmentation process. FCN includes an encoder and decoder architecture that produces the output as the same size as the input. A new augmented data was developed and named Random Crop and Fill(RCF) in [11].

For biomedical images, U-Net is one of the most popular and commonly used FCNs. As it skips the connection between the encoder-decoder to recover the spatial reference loss in the downsampling process, it produces more accurate segmentation results [10] [12]. Preprocessing steps for the training datasets included CLAHE, gamma adjustment, standardization, and grayscale conversion [13]. Numerous academics have developed a variety of U-Net topologies based on deep learning (U-Net, Residual U-Net, R2U-Net, ladder net, etc). The results of other U-Net-based architectures are contrary to the U-Net architectures [2]. Following this, various preprocessing methods and denoising techniques were developed to remove noise in the input images. These techniques include Gaussian and mean filters, etc. The resulting images were subjected to two post-processing techniques: filling container gaps and removing artifacts. This was done because output images had some gaps which were miscategorized as non-vessels [14].

The sensitivity rate was lower for the procedure described in [15]. The CLAHE+CNN model was proposed for the segmentation of the retinal blood vessels. CNN is used for feature extraction after image enhancement using CLAHE. While the proposed method outperforms other similar current studies, it provides a more accurate diagnosis of diabetic retinopathy. Although various methods discussed here gave exceptional results in various aspects, there remain a few areas which need improvement.

## III. DATASET

Many researchers and deep learning specialists use publicly available datasets to develop the retinal blood vessel segmentation algorithm. Three data sets (DRIVE, CHASE DB1, and HRF) were used in this paper. The DRIVE data set and its ground truth are divided into 20 testing and 20 training fundus images. In addition to its ground truth, 28 fundus images make up the CHASE DB1 dataset. HRF dataset includes 45 fundus images along with its ground truths. In this paper,the DRIVE and CHASE dataset is augmented and used for training whereas, the HRF dataset is used for testing.

## IV. METHODOLOGY

The architecture for the segmentation procedure in this paper is a convolutional neural network based on U-Net [13]. Figure 1 depicts the entire process of segmenting the retinal blood vessels. It is divided into two phases: segmentation and pre-processing. Green channel selection [6] [14], data augmentation, and CLAHE are three steps of pre-processing. To achieve effective results, the final step is to segment the retinal blood vessels.

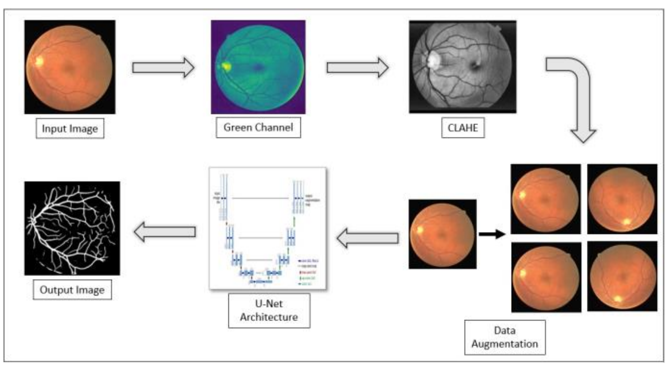


Fig. 1. Pipeline of segmentation process

### A. PRE-PROCESSING

Pre-processing is a vital step for improving the quality of input images to achieve better segmentation performance. The datasets to be used as input images are DRIVE and CHASE datasets consisting of a total of 48 fundus images. The following are the steps that are done in the pre-processing of retinal fundus images.

*1) Green channel selection:* Retinal fundus images which are usually in RGB (Red, Green, Blue) are converted to grayscale images. In RGB, the green channel carries more information about blood vessels and also gives better results compared to blue and red channels.

*2) CLAHE:* This is widely used method in medical imaging to improve the contrast and quality of retinal fundus images An example of its application includes retinal blood vessel segmentation [11] and other such methods. Alternatively, both Histogram Equalization and Adaptive Histogram Equalization techniques can be used in improving blood vessels in fundus images for segmentation processing. After the green channel selection process, CLAHE is performed. [4] [6] [11] [13]

*3) Data Augmentation:* For segmentation of retinal blood vessels, augmentation [5] [6] is a common technique in deep learning methods such as CNN, U-Net, etc. It involves growing the amount of the few training or testing datasets that are currently accessible. In U-net-based convolutional neural networks, augmentation is a crucial stage since limited data is insufficient for training and to prevent overfitting. To overcome the problem of overfitting, augmentation is done.As mentioned in the dataset section, we are using DRIVEand CHASE datasets for training. We applied augmentation techniques like cropping, rotating, and mirroring on the input images [4], and resized them to 512*512 size. As each image gives 4 augmented images, hence, a total of 80 and 112 images along with the ground truth of DRIVE and CHASE DB1 datasets respectively are generated and used for training.

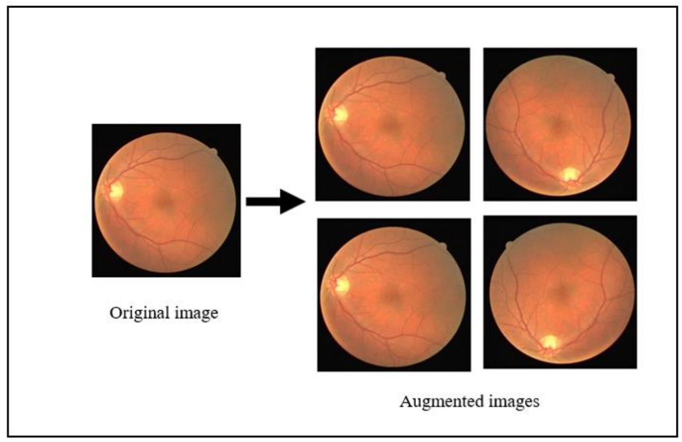


Fig. 2. Data augmentation

### B. U-NET ARCHITECTURE

By Ronneberger, et al. in 2015 U-net architecture [12] [13] [14] was proposed to aim for better retinal blood vessel segmentation. The U-net architecture is shown in Figure 3. It consists of three parts:

1) Contraction path(encoder)(down-sampling)
2) Bottleneck
3) Expansion path(decoder)(up-sampling)

The contraction path (down-sampling) is responsible for the extraction of features from the input image. This isdone by two operations, convolutional and pooling. Pooling helps in lowering the spatial resolution of feature maps, while convolutional operations aid in the extraction of abstract features. The four blocks that make up the encoder path are a 3*3 convolutional layer, a 2*2 max pooling layer, and an activation function with batch normalization. During down-sampling for each pooling operation, feature maps will be doubled. The bottleneck is a path between down-sampling and up-sampling with 2 convolutional layers. The expansion path is responsible for reconstructing the segmented image from the feature maps which are extracted by the encoder path.

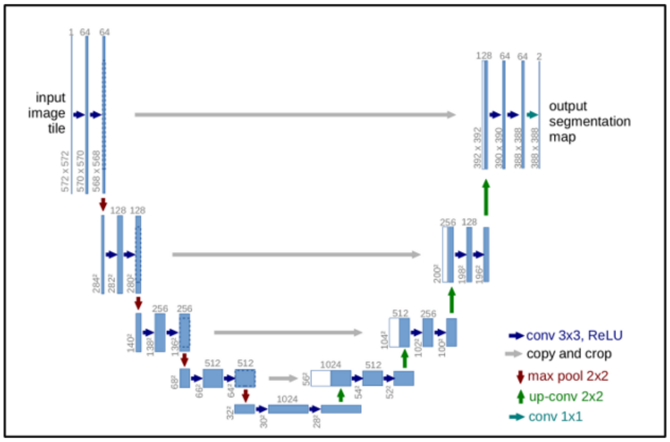


Fig. 3. U-net architecture

This is done by two operations, transposed convolutional and up-sampling. Transposed convolutional operation increases the spatial resolutions of feature maps and the up-sampling operation repeats each pixel in feature maps. Upsampling characteristic maps a 2*2 convolution that halves the function maps and 3*3 convolutions, each reduced by using a ReLu, are the steps in the decoder path. To connect characteristic maps in encoder blocks to different feature maps in encoder blocks, the U-net skip connections are present. They resource in enhancing accuracy by allowing the decoder block to get admission to high-level features from the encoder block. In the remaining layer, each sixty-four-component characteristic vector is mapped to the required range of classes using a1*1 convolution. Thus, this network has a complete of 23 convolutional layers.

## V. RESULTS AND DISCUSSION

This section describes how the proposed method was used for the training and testing of specifics. The model was trained using the Nvidia Rtx A6000 GPU available at the maker space of the university [16]. Our first assessment was on the effects of different phases of image preprocessing. The fundus image's green channel is extracted and used to produce the segmented output. The outcomes are shown in Figure 4. The results achieved by the proposed method using different parameters are shown in Table 1.

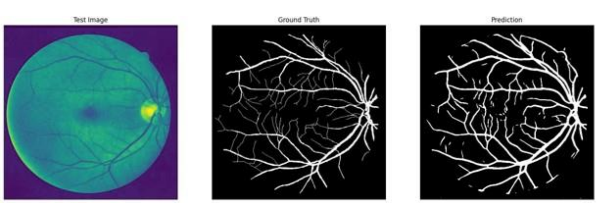


Fig. 4. U-net Segmentation result

TABLE I
PARAMETER OF ACCURACY BEFORE AUGMENTATION

| DATASET | AVERAGE ACCURACY |
|---|---|
| DRIVE | 0.914 |
| CHASE DB1 | 0.892 |
| DRIVE+CHASE DB1 | 0.903 |

TABLE II
PARAMETER OF ACCURACY AND MEAN IOU AFTER AUGMENTATION

| DATASET | AVERAGE ACCURACY | MEAN IOU |
|---|---|---|
| DRIVE | 0.932 | 0.739 |
| CHASE DB1 | 0.904 | 0.672 |
| DRIVE+CHASE DB1 | 0.918 | 0.705 |

The results got slightly better after performing the augmentation process. The model is evaluated for its performance using an accuracy-mean IoU curve. The value of testing and training data rises regularly.

The IoU (Intersection over Union), also known as Jaccard's Index, is an important measure of segmentation models. It helps us understand how well a model can recognize and separate objects from their surroundings in an image. It helps improve accuracy by showing how well they match. A higher IoU indicates a better match between prediction and reality. This is a way to fine-tune the images to get the exact results.IOU measures how two shapes overlap by comparing their shared area with the total area they cover together.

## VI. CONCLUSION

This paper proposes a U-Net-based convolutional neural network architecture for the segmentation of retinal blood vessels. The preprocessing steps of the method include segmentation, CLAHE, and grayscale transformation. Compared with the CHASE DB1 dataset, better performance is achieved for the DRIVE dataset as shown in Table 2, with an average accuracy of 0.932. As we can see in Tables 1 and 2, the average accuracy increases as we increase our dataset size, so the augmentation process is necessary for better results. This leads us to conclude that U-net-based CNN is suitable for the production of retinal images in other medical applications We can be confident that if noise removal was applied using raw images in pre-processing internally, the results would be far better. The aim is to tune the network parameters to obtain better results in future work.

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